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A spectral mixture analysis approach to quantify Arctic first-year sea ice melt pond fraction using QuickBird and MODIS reflectance data

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ABSTRACT

Melt ponds play a significant role in the summer decay of sea ice due to the fact that their albedo is significantly lower than surrounding snow and sea ice surface. Despite its requirement for thermodynamic sea ice modeling, measurement of melt pond areal coverage using satellite remote sensing has proven difficult due to significant spatiotemporal variability in the timing and evolution of melt ponds. Less than optimal results from prior studies employing a spectral mixture analysis (SMA) towards the determination of melt pond areal coverage from satellite remote sensing data provided the incentive for a multiple endmember spectral mixture analysis (MESMA) approach. The MESMA was performed on Moderate Resolution Imaging Spectroradiometer (MODIS) imagery using endmember spectra obtained from atmospherically corrected coincident high resolution imagery, surface observations and modeling. Results were validated against a high resolution Quickbird image acquired coincident to the MODIS image. The validation indicates that the best MESMA results provide consistent estimates of melt pond coverage for regions with high pond coverage (within 5% melt pond coverage) but overestimate pond fraction for regions with low pond coverage (by 10% or more). This may be due to deficiencies in the representation of sea ice surfaces within the endmember library used, oversimplified modeling of the ice surface and shortcomings in the validation process. However, it is assumed that with further refinement, the MESMA technique could allow for reliable estimates of the areal coverage of sea ice melt ponds using low resolution (large spatial coverage) optical satellite imagery under a wide variety of spatiotemporal pond evolution and fraction conditions.

1. Introduction and background

The Arctic sea ice cover plays a crucial role in the Earth's climate system by moderating the absorption of solar energy and the heat flux at the atmosphere-ocean interface (Curry and Schramm, 1995; Eicken and Lemke, 2001; Serreze and Stroeve, 2015; Kapsch et al., 2016). Sea ice reflects incident energy from the sun, ~5–8 times greater than from open water, demonstrating that open water areas stimulate an ice-albedo feedback that act to accelerate the rate of adjacent sea ice melt (Curry et al., 1996; Barry, 1996; Eicken and Lemke, 2001; Perovich et al., 2007). In recent years, record minimums of Arctic sea ice extent and thickness have been observed coincident with warmer surface temperatures, longer melt seasons, and a decreased surface albedo during the summer months (Stroeve et al., 2005; Devasthale et al., 2013; Kang et al., 2014; Kwok and Cunningham, 2015; Lindsay and Schweiger, 2015; Kapsch et al., 2016).

Stand-alone and coupled sea ice models that successfully replicate observed changes in the seasonal cycle of sea ice growth and melt provide useful tools for exploring and understanding their controlling processes (Steele and Flato, 2000; Makshtas et al., 2003). Modeling facilitates sensitivity analyses which reveal potential sources of change in sea ice volume and extent - e.g., atmospheric circulation, ocean heat flux, surface albedo, ice dynamics and surface air temperature (Ebert and Curry, 1993; Steele and Flato, 2000; Makshtas et al., 2003; Liu et al., 2007; Flocco et al., 2010; Flocco et al., 2012; Skyllingstad et al., 2015). The ability of these models to replicate the seasonal growth and decay of the sea ice volume is inhibited by inadequate parameterizations of ice surface albedo during sea ice ablation. Though necessary due to scarcity of observations, simplistic sea ice albedo parameterizations are unable to capture the highly dynamic and heterogeneous surface albedo evolution during seasonal spring and summer melt periods (Hanesiak et al., 2001; Perovich et al., 2002). Melt pond

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fractions on summer sea ice have been observed to change dramatically (from as low as 15% to 85%) on spatial scales that are on the order of tens to hundreds of meters (Barber and Yackel, 1999; Hanesiak et al., 2001). Additionally, melt pond fraction is generally greater in the case of FYI (~20–60%) when compared to MYI (~ < 30%) (Eicken et al., 2004; Landy et al., 2014; Landy et al., 2015), owing to greater spreading of ponds over FYI, with relatively flat topography. Under current Arctic FYI conditions, greater melt pond fraction leads to earlier sea ice break up due to enhanced ice surface melting and within the ice volume (Arntsen et al., 2015) especially when induced by summer storms (Kohout et al., 2014), and may significantly delay sea ice freeze-up (Vihma, 2014).

Melt ponds are a dominant feature of the spring-summer sea ice albedo evolution. Low albedo ponds (~15 to 30%), with a maximum areal coverage on first-year sea ice (FYI) of ~20–60%, accelerate sea ice melt by as much as 2.5 times (Barry, 1996; Fetterer and Untersteiner, 1998; Hanesiak et al., 2001). Accelerated melt leads to an earlier ice-free season, which has been shown to be an important factor in the growth rate and extent of sea ice in the subsequent winter (Curry and Schramm, 1995; Laxon et al., 2003). For relatively smooth landfast FYI – the focus of this paper – melt ponds form from snow melt once air and snow temperatures rise above freezing and snow melt water begins to accumulate in depressions on the surface caused by antecedent winter snow drift and surface wind conditions (Iacozza and Barber, 1999; Yackel et al., 2000; Hanesiak et al., 2001; Scharien and Yackel, 2005). A positive feedback between lower albedo snow on the thin snow patches – a result of enlarged snow grains formed from snow metamorphism (Hanesiak et al., 2001), causes the melt ponds to grow in these depressions at the expense of water drainage from the slightly elevated, finer grained and higher albedo snow or bare ice patches (Holt and Digby, 1985; Iacozza and Barber, 2001). Melt pond areal coverage, termed 'pond fraction' (F_P), evolves as a spatially and temporally heterogeneous patchy network of snow or bare ice areas and melt ponds due to the complex interplay of melt water production, e.g., via variable snow thickness distributions; and meltwater drainage mechanisms through ice of varying permeability and hydraulic head (Freitag and Eicken, 2003; Eicken et al., 2004; Scharien et al., 2012; Scharien et al., 2014; Landy et al., 2014).

In order to improve melt rate estimates in sea ice and climate models, the parameterization of surface albedo must account for the spatial and temporal distribution of F_P (Fetterer and Untersteiner, 1998; Hanesiak et al., 2001; Perovich et al., 2002; Yackel et al., 2007). One way to improve the parameterization of F_P is to apply updates based on near-real time remotely sensed observations. Spaceborne remote sensing can be used to effectively detect lead (or open water) fractions (e.g. Willmes and Heinemann, 2015; Wernecke and Kaleschke, 2015), but less success has been achieved for F_P. For example, various classification and statistical detection methods including thresholding, principal component analysis and artificial neural network approaches have been applied to coarse resolution optical satellite imagery such as MODIS, MERIS and VIIRS to derive F_P, but with limited success (Perovich et al., 2002, Markus et al., 2003; Tschudi et al., 2008; Rösel and Kaleschke, 2011; Rösel and Kaleschke, 2012a, 2012b; Istomina et al., 2015; Istomina et al., 2015). This is primarily due to the fact that melt ponds are typically of a spatial scale that is sub-resolution of these sensors (Perovich et al., 2002) thereby necessitating a decomposition algorithm to extract sub-pixel F_P variations from mixed pixels. While recent results are promising (eg. Tanaka et al., 2016), passive microwave techniques remain largely limited by the sub-resolution problem. And while active microwave remote sensing approaches the necessary spatial resolution (e.g., Yackel et al., 2000b; Scharien et al., 2014; Han et al., 2016; Fors et al., 2017), these still requires further validation.

The primary objective of this study is to assess the use of Multiple Endmember Spectral Mixture Analysis (MESMA), as a method to quantify the fractional coverage of melt ponds on landfast FYI. A MESMA will be used to unmix $F_P$from Moderate Resolution Imaging Spectroradiometer (MODIS) imagery, where melt ponds are sub-resolution of the sensor. The performance of the MESMA will be evaluated against $F_P$derived from coincident high resolution QuickBird (QB) imagery, where melt ponds are similar to the spatial resolution of the sensor. We follow with a description of the MESMA approach.

2. Multiple Endmember Spectral Mixture Analysis (MESMA)

Spectral mixture analysis (SMA) is one of several techniques, including aerial photo interpretation (Fetterer and Untersteiner, 1998; Perovich et al., 2002), processing of aircraft based videography (Barber and Yackel, 1999; Yackel et al., 2000; Tschudi et al., 2001; Markus et al., 2003) and analysis of microwave backscatter (Yackel and Barber, 2000; Scharien et al., 2007; Scharien et al., 2010; Scharien et al., 2012; Scharien et al., 2014), that can potentially improve quantification of $F_P$and its distribution on sea ice (Markus et al., 2003; Tschudi et al., 2003; Rösel and Kaleschke, 2012a, 2012b). SMA is used to extract surface-type fractions of a heterogeneous mix of sub-pixel features or surface types occurring within a mixed pixel by decomposing their relative reflectance contributions. SMA assumes that the spectral signatures of surface cover types occurring within a mixed pixel form a linear equation weighted by their areal coverage, determines the spectral response for the pixel that is detected by a sensor. Most applications of SMA assume that mixing is linear (Keshava and Mustard, 2002) which means the reflectance value for each pixel is an area weighted average of the reflectance contributions from surface types within the pixel. Each surface type, or endmember, is assumed to have a distinct spectral signature which describes how it interacts with (i.e., reflects) incident solar radiation at certain wavelengths. This technique has been applied successfully to the quantification of melt pond cover in previous studies such as those by Markus et al. (2003) and Tschudi et al. (2003, 2005). One of the sources of error in the model noted by Tschudi et al. (2003, 2005) was in the representation of the melt pond endmember. They needed to average two different pond types (blue and green spectrum) in order to fit the constraints set by the number of bands available.

One technique that can address this problem is Multiple Endmember Spectral Mixture Analysis (MESMA) demonstrated by Roberts et al. (1998). It assumes that for each pixel, there can be multiple combinations of endmembers and that the best one can be chosen based on some criteria measuring model fit (Roberts et al., 1998). While Roberts et al. (1998) state that either band residual terms or model RMSE can be used, more recent studies of Dennison and Roberts (2003), Dennison et al. (2004), Li et al. (2005) and Ballantine et al. (2005) rely strictly on the RMSE. Once a pixel has been unmixed, a reconstructed spectral observation can be created based on the obtained areal fractions of endmembers and their spectra. Unless a model is completely perfect, differences (residuals) will be present between the observed spectral observation and the modeled spectral observation for each band used in the SMA. The RMSE is the combined effect of these errors as demonstrated in Eq. (1) (Dennison et al., 2004).

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{\lambda=1}^{M} r_\lambda}{M}} \tag{1}$$

where r_λ is the residual for band λ and M is the number of bands. Since RMSE is assumed to be an indicator of a model's failure to match the original observation, the lower the RMSE, the more suitable the model. Other criteria that can be used to aid in the selection of endmembers for MESMA include exclusion of models that produce unrealistic endmember fractions (ideally these will all be between 0 and 1) and exclusion of models where residuals exceed a certain threshold for a set of contiguous bands (Roberts et al., 1998).